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Design of Breast Ultrasound Image Segmentation Model Based on Tensorflow Framework

Dafeng Gong

Department of Information Technology, Wenzhou Vocational & Technical College, Wenzhou, China

289133894@qq.com

Abstract: In order to achieve accurate segmentation of 3D breast ultrasound image, combining the algorithm of convolutional neural network using TensorFlow framework technology, a method of automatic segmentation of breast ultrasound images is put forward. When using the trained model to segment ultrasonic image, image block is identified by each pixel to determine each pixel category, thus to get the final segmentation result. Experiments show that the method proposed can correctly distinguish multiple tissue regions in breast ultrasound images and has achieved good results in terms of various quantitative indicators. Finally, the optimal model is selected by comparing the segmentation results generated by different neural network parameters.

Keywords: TensorFlow, mammary gland, ultrasonic image segmentation, convolution neural network.

1. INTRODUCTION

Breast cancer is one of the most common cancer found in women. Early diagnosis and treatment of breast cancer can effectively improve the cure rate of breast cancer [1]. In the clinical diagnosis of breast cancer, biopsy is the most accurate and authoritative medical means. However, biopsy, as an invasive method, will inevitably cause physical and mental harm to patients [2,3]. The rapid development of medical imaging technology provides a new method for the detection of breast cancer. Doctors can observe the lesion area from the image and carry out analysis and diagnosis. At present, the medical imaging technology that can be used for breast tumor detection includes ultrasound imaging, molybdenum target X ray imaging, magnetic resonance imaging (MRI), positron emission computed tomography (PET) and so on. Among them, the cost of MRI and PET is the highest and has a certain side effect of radiation, which is generally not suitable for the general survey of breast tumor. At present, in the clinical practice of breast cancer detection, the combination of X-ray examination and ultrasound examination is usually used.

Compared with the above several imaging technologies, the breast ultrasound image has the following characteristics: first, compared with steel saturation X ray, MRI, PET and other technologies, ultrasound has no radioactivity and has little effect on patients' health. Second, ultrasound imaging can display most of the lesion area, and for the dense breast tissue, ultrasonic image detection has a better effect. Third, the ultrasound images can show the various sections of the breast tissue, while the molybdenum target X-ray images can only show the specific section. Fourth, the cost of ultrasonic imaging is the lowest and the price ratio is high. Breast ultrasound imaging technology, for a variety of advantages above, has become one of the most important means for the detection of breast cancer, but there are also some disadvantages, compared with other imaging techniques, ultrasound image has the disadvantages of speckle noise, low contrast and poor resolution, fuzzy organizations and organs in the image boundary, some tumors on the surface and the surrounding normal ones are very similar, it is difficult to distinguish between different individuals, in addition to the differences between breast cancer types. For these reasons, the doctor needs rich clinical experience for breast ultrasound image judgment and understanding [4,5]. The doctor in the course of clinical diagnosis of breast ultrasound image interpretation is very subjective, many doctors will have a different interpretation and understanding of the same breast ultrasound image, it is difficult to form a uniformed diagnosis; another disadvantage is that the interpretation workload of breast ultrasound image is large, artificial processing depends entirely on the doctor's judgement while they are prone to fatigue, leading to the rise of misdiagnosis rate.

To sum up, it is necessary to use the computer aided diagnostic technique (CAD) to help doctors to interpret and diagnose the ultrasound images of the mammary glands. CAD technology can reduce the workload of doctors, improve the objectivity and accuracy of breast ultrasound examination and helps further diagnosis and treatment. Image segmentation is an important part of the breast ultrasound CAD system.

2. LITERATURE REVIEW

Image segmentation refers the division of images according to the pixel feature (grayscale and texture) image into a series of non-overlapping regions. It is the fundamental task of image analysis, also an essential part of the computer aided diagnosis system. The ultrasound image segmentation results directly affect the subsequent analysis and processing of tumor cells [6]. Ultrasound images have inherent defects such as low resolution, low contrast and high speckle noise. These defects largely reduce the quality of ultrasound imaging, resulting in the difficulty of segmentation of ultrasound images, and the same with breast ultrasound images. In the segmentation of ultrasound images, traditional image segmentation algorithms, such as edge detection, histogram threshold and region growing, are generally difficult to get ideal results. In recent years, domestic and foreign scholars have done a lot of research on segmentation of breast ultrasound images, made a lot of improvements and integration in traditional image segmentation technology, and proposed many segmentation methods of breast ultrasound images. The segmentation of three-dimensional breast ultrasound images is also a hot spot in the field of breast ultrasound image analysis. Related scholars put forward a semi-automatic three-dimensional breast image segmentation method. First, we filter the noise and enhance the edge processing, then use the three-dimensional discrete gradient vector flow active contour model to achieve the extraction of breast tumor boundaries. In addition, some scholars proposed a segmentation method of automatic 3D breast ultrasound image. It first uses morphological reconstruction method for image pre-processing and noise suppression to improve the quality of the image, then extracts the 3D image edge information using 3D Sobel operator, and then uses the watershed algorithm to segment the 2D image in the image sequence, and finally classify the area using threshold method, the method can be used for the image segmentation of skin, fat, gland and tumor and other parts.

Most of the existing methods can achieve good results in the segmentation of breast ultrasound images, but they also have some shortcomings in the process of segmentation. Non-automatic segmentation method generally relies on manual intervention guidance, such as the initial outline, set the clustering number and also the delineation of the region of interest, manual operation is subjective and of low efficiency. All these makes it not conducive to the promotion and application in practice; automated segmentation technology needs to be integrated into the corresponding method of prior knowledge. The doctor's subjective prior knowledge is used to guide the segmentation, but it is difficult to use precise mathematical terms defined. There are also differences between ultrasound images in practical diagnosis—almost impossible to use a generic method for all image segmentation. In this paper, based on this practical problem and combining the theory of machine learning, the automatic segmentation of breast ultrasound images with a certain generality is realized.

3. METHODOLOGY

3.1 TensorFlow framework

TensorFlow is an open source software library that uses data flow graph for numerical computation. Its flexible architecture enables it to be calculated on multiple platforms, such as one or more CPU or GPU of a computer, or server cluster, mobile device and so on. TensorFlow was originally developed by researchers and engineers from Google Brain team. It is used for machine learning and deep neural network research, but the versatility of the system makes it widely used in other computing fields.

TensorFlow is calculated by data flow graph. Nodes in the data flow graph are used to represent some mathematical operations. The lines in the graphs are used to describe the multidimensional data array, Tensor. The name of Tensorflow is derived from the calculation of the flow of calculation through the flow of Tensor in a data flow graph.

Google opened the TensorFlow framework in November 2015, and then quickly got the response of many companies and developers. TensorFIow has the main advantages:

First, the high flexibility. TensorFlow is not entirely designed for neural network. As long as computing can be represented as a data flow graph, Tensorflow can be used. When required for rapid development, Python can be used for quotient Abstract Programming, and C++ can be used to enrich the underlying operations when high performance is required.

Second, portability. Tensorflow can run on CPU or GPU, and the same code can be easily transplanted to various devices, PC, server or mobile devices.

Third, the combination of research and application. Due to the design of the degree abstraction, using Tensorflow can enable application researchers to quickly apply ideas to products and enable academic researchers to share code directly and improve the output of scientific research.

Fourth, automatic computing. Gradient based machine learning algorithms will benefit from the ability of Tensorflow automatic computing. When using TensorFlow, only the model structure and the target function are defined, the input data is added, and the Tensorflow will automatically perform most of the operations.

Fifth, multilingual support. Tensorflow provides the Python and C++ programming interfaces and can choose one language for programming arbitrarily.

Sixth, high performance, Tensorflow has good support for operation of threads, queues, asynchronous operations and so on, which can maximize the computing potential of hardware resources. Tensorflow can assign computing nodes in the data stream map to different devices and automatically implement parallel computing.

Because of the above advantages and the advantages of open source and active communities, this paper chooses to use TensorFlow framework to train and predict neural network. The GPU support version of TensoFIow's Windows platform is selected, and NVIDIA graphics card driver, CUBA toolkit and cuDNN (CUDADeepNeuralNetwo out) library are needed to support GPU operation. In addition, the experiment uses Python as the programming language of the neural network and uses Matlab to process the data.

3.2 Experiment approach

Segmentation of breast ultrasound images can be regarded as a pixel classification problem. By identifying the categories of each pixel in the image, the segmentation of the whole image can be achieved. The pixels belong to the category is determined by the pixel block as the image block, as shown in Figure 1.

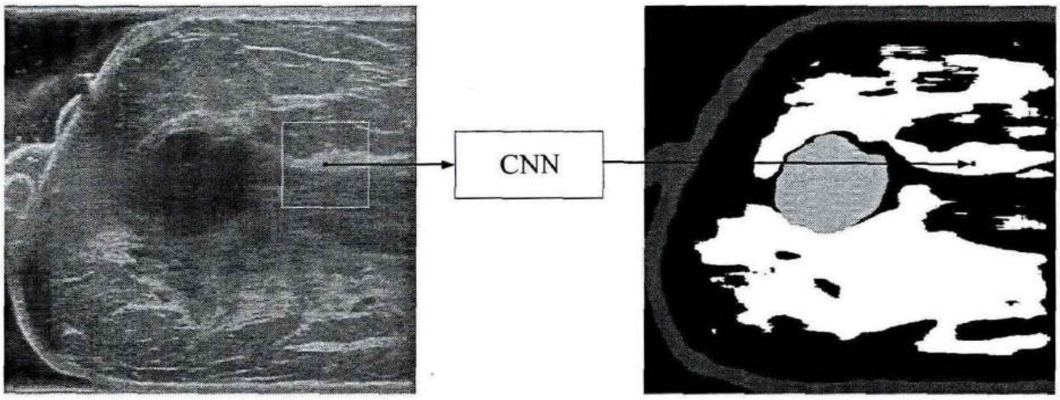

Figure 1. Experiment approach

Convolution neural network is used to realize this classification problem. The input of convolution neural network is an image block, and the output is the category of the central pixel of the image block. First, use the image that the doctor annotated, build the sample library, build training data set and test data set, then use training data set to train neural network and evaluate training parameters on the test set. If the performance of the neural network in the test set is good, it can be used for other image segmentation, the whole image in pixels sequentially forms image block. Image block through the calculation of the neural network produces the corresponding pixel of the category, which can realize the image segmentation. The experimental process is shown in Figure 2.

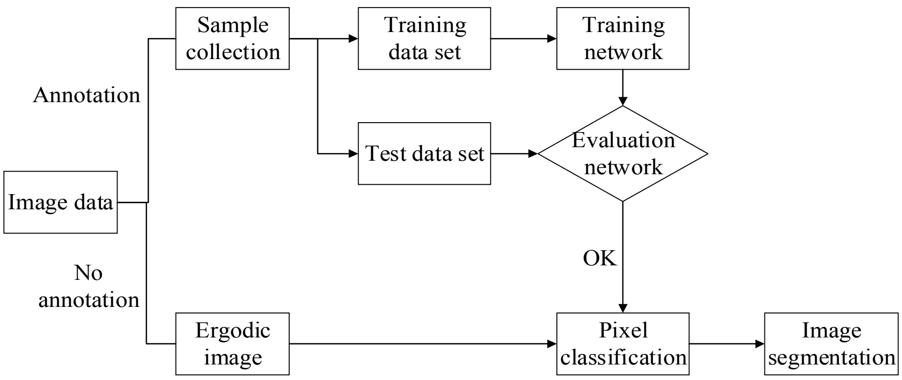

Figure 2. Experiment procedure

3.3 Sampling

There are 58 images manually tagged by doctors, including 27 tumors and 31 non-tumors. Each image annotation area includes skin, gland and tumor. Different gray values are used to annotate the new layer corresponding to the original image.

The acquisition of data, by reading the annotation of the pixel gray value acquisition layer pixels corresponding to the categories in the original image in the selected image block to the corresponding pixel of image, beyond the scope of point 0 instead of pixel values, then pixel image fragment contains set of normalized (divided by 255). As a convolution of the input of the neural network, pixel corresponding categories can be expressed by 4 categories, according to the label, with the number 0 to represent glands, with the number 1 represents tumor, with the number 2 skin, with the number 3 other parts (usually fat). The digital K specifically expressed as the only in the K dimension (from 0) figures for the four-dimensional vector 1 to facilitate the treatment of the neural network, gland is expressed as [1,0,0,0], tumor expressed as [0,1,0,0], skin expressed as [0,0,1,0] and other parts expressed as [0,0,0,1].

The size of the image block selected in the experiment is 128*128; the input from the convolution neural network is 128*128 normalized matrix; the output is a four-dimensional vector. In each image containing tumor, 8000 feature pixels were selected; 6000 feature pixels were selected from the image without tumor. Finally, 402000 samples were generated, 300000 samples were selected as training set, and the rest was used as test set.

3.4 The design of convolution neural network

The structure of the convolution neural network designed for classification task is shown in Figure 3. It is an 8-level network, including input layer, convolution layer 1, pooling layer 1, convolution layer 2, pooling layer 2, convolution layer 3, pooling layer 3, full connection layer and output layer.

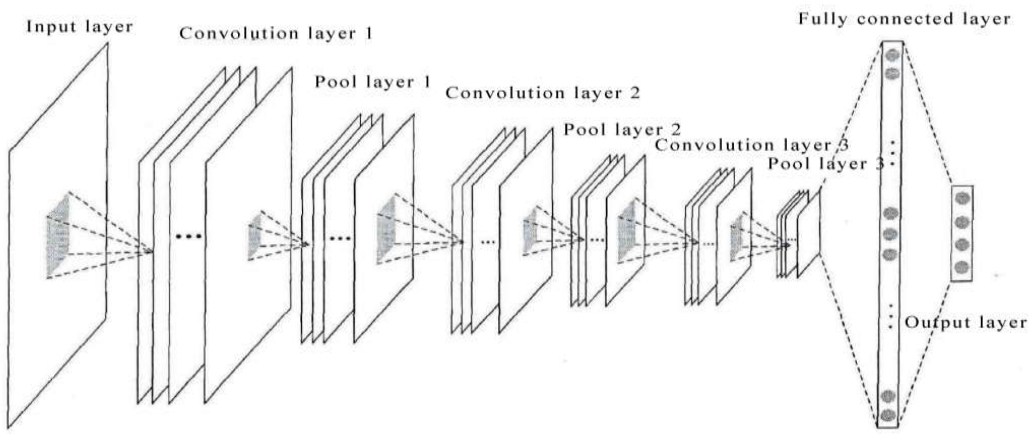

Figure 3. The structure of convolution neural network

The input layer: The 128*128 image block of the input layer of the convolution neural network is a 128*128 matrix formed after the normalization of the set of pixels.

Convolution layer 1: Convolution layer 1 uses 36 convolutions of 7*7 to convolute the input image, and outputs 36 feature maps, that is, 36 different features are extracted from the input image. The sliding step of the convolution operation is 1 pixels, and the size of each feature map after convolution is (128-7+l) * (128-7+1) =122*122. Convolution layer 1 has 36 convolution kernels, each convolution kernel has 7 x 7=49 weights and 1 bias parameter, so the convolutional layer 1 needs a total training parameter of (7*7+l) * 36=1800.

Pooling layer 1: The size of the sampling area of pooling 1 is 2*2, and the maximum value of no overlap is applied. The size of each feature map is changed to 61*61 and the number of features is the same as that of convolution layer 1, 36.

Convolution layer 2: The convolution layer 2 has 36 different features for the 1 output of the pooling layer, that is, the number of convolution kernel is 36, and the size of each convolution kernel is 6*6. Each convolution kernel has 6*6=36 weights and 1 bias parameter, with a total of 36 convolution kernel, so the parameter of the convolution layer 2 needs to be trained (6*6+l) *36=1332. Because the size of the characteristic map of the 1 output of the pool layer is 61*61 and the sliding step length of the convolution operation is 1, so the size of the characteristic map of the output of the convolution layer 2 is (61-6+l) * (61-6+1) =56*56.

Pooling layer 2: The pooling layer 2 uses the same way as the pooling layer 1 to maximize the pooling operation of the feature map of the convolution layer 2 output, and the size of each characteristic map is changed to 28*28.

Convolution layer 3: The number of convolution nuclei in convolution layer 3 is 64, the size of convolution kernel is 5*5, and the sliding step of convolution operation is 1. The size of the feature map of the output of the pool layer 2is 28 * 28, and the size of the feature map is changed to (28-5+1) * (28-5+l) =24*24 after the convolution. The number of the feature map is 64. The parameters of the convolution layer 3 need to be trained is (5*5+1) *64=1664.

Pooling layer 3: The pooling layer 3 uses the maximum 3*3 pool and the sliding step is 3, that is, no overlapping sliding, and the size of the feature map is 8*8, and the number is constant.

Fully connected layer: The number of neurons in the full connection layer is set to 1024, because the size of the feature map is 8*8 and the number is 64. The number of eigenvectors of the input full connection layer is 64*8*8, the number of output neurons is 1024. The number of neurons in the connected layer is 8.

The output layer: Neuron output layer is determined according to the actual classification task, because there are 4 categories of training samples, so set the output node layer neuron number as 4, the output of the layer in fully connected layer is mapped to a 4-dimensional variable, and then use the Softmax function to achieve the classification and output probability distribution.

Convolution layer and full connection layer all use ReLU as activation function, because ReLU function has more advantages in optimizing network parameters than traditional Sigmoid functions and tanh functions, and the computation is simpler, which can improve the efficiency of training.

In order to reduce the problem of over fitting, the Dropout method is used between the full connection layer and the output layer of the convolution neural network. In the training process, the proportion of Dropout is set to 0.5, and the proportion of Dropout is set to 0 in the test process, which is to close the Dropout.

4. EXPERIMENT RESULT AND ANALYSIS

4.1 Evaluation standards

Regional based assessment.

Image segmentation performance evaluation based on region uses accuracy rate, precision rate, recall rate and Fl-measure as quantitative indicators respectively. Based on the segmentation of tumors as an example, in a test image, the pixel represents tumor comparison model of convolutional neural network of the detected image set and the actual tumor (with manual segmentation results as the standard) pixels set evaluation model for tumor segmentation effect.

First, explain some of the related concepts, as shown in Table 1:

Table 1. Description of the relevant concepts in the evaluation index

Classes	Tested to be tumor	Tested to be non-tumor
Tumor predicting	True Positive(TP)	False Positive(FP)
Non-tumor predicting	False Negative(FN)	True Negative (TN)

Among which:

True Positive (TP): represents the affirmation of tumor predicted to be true, which is the number of tumor pixels in the correct judgment;

False Positive (FP): represents the affirmation of tumor predicted to be false, which is the number of tumor pixels in the false judgment;

False Negative (FN): represents the negation of tumor predicted to be false, which is the number of tumor pixels in the missed in the judgement;

True Negative (TN): represents the negation of tumor predicted to be true, which is the number of tumor pixels in the correct judgment;

We can have the following with the above information:

$$Accuracy = \frac{\text{The number of pixels that are correctly judged}}{\text{The total number of pixels in the image}} = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$\Pr ecision = \frac{\text{Correctly judged the number of tumor pixels}}{\text{The total number of detected tumor pixels}} = \frac{TP}{TP+FP} \quad (2)$$

$$\operatorname{Re} call = \frac{\text{Correctly judged the number of tumor pixels}}{\text{The actual total number of tumor pixels}} = \frac{TP}{TP+FN} \quad (3)$$

$$F1-measure = 2\times\frac{precision\times\operatorname{Re}call}{precision+\operatorname{Re}call} \quad (4)$$

In the case of imbalance between positive and negative samples, it is very difficult to use the accuracy only as an evaluation index. It is unlikely that there will be much pixels representing tumor in a gland ultrasound image. There may be only one percent among the all possibility. If only use the accuracy as the evaluation index, even if all the negative predictive model class (non-tumor), the accuracy rate can reach 99%, such assessment has no meaning, which also needs several other evaluation indices to complete evaluation.

Accuracy is a measure of how likely the model is to predict the correct positive class. The recall rate is the correct prediction of the model, to what extent does the positive class include the real positive sample. In a popular language, the accuracy rate is to ‘find the right ones’, and the recall rate is to ‘find each and every in that class’. The F1 value is the harmonic mean of the accuracy rate and the recall rate. The F1 value will be high when the accuracy and recall are high.

Boundary based assessment.

The performance evaluation of image segmentation based on boundary shows the similarity between the segmentation results of the convolutional neural network and the standard results of hand segmentation by doctors. The Hausdorff distance (HD) is used as the criterion. First, the edge is extracted from the results of automatic segmentation and manual segmentation. A and B respectively represent the set of boundary pixels, which are automatic segmentation and manual segmentation. The formula of Hausdorff distance is as follows:

$$H(S,G) = \max\{\max_{a\in A}\{\min_{b\in B}\{d(a,b)\}\}, \max_{b\in B}\{\min_{a\in A}\{d(a,b)\}\}\} \tag{5}$$

In this, d(a, b) represents the Euclidean distance between pixels a and b. The smaller the Hausdorff distance is, the more similar the shape is, and the more accurate the result of the segmentation is.

4.2 Experiment result

According to the above method, the segmentation task of breast ultrasound image is transformed into image block-based classification problem. Convolution neural network is deployed to extract feature blocks and classify them. In the use of the trained model on the image segmentation, the image pixels are chosen according to the image pixels. Each image block serves as the input of the neural network, the output value is the category predicted by the model. The segmentation finishes when the categories of each pixel in the image are realized. Figure 4 is the use of the trained neural network model for image segmentation. Different grey value of each pixel is used in the image to classify. In the first column is the original ultrasound images, the second column is the standard manual segmentation, the third column is the use of convolution neural network model segmentation.

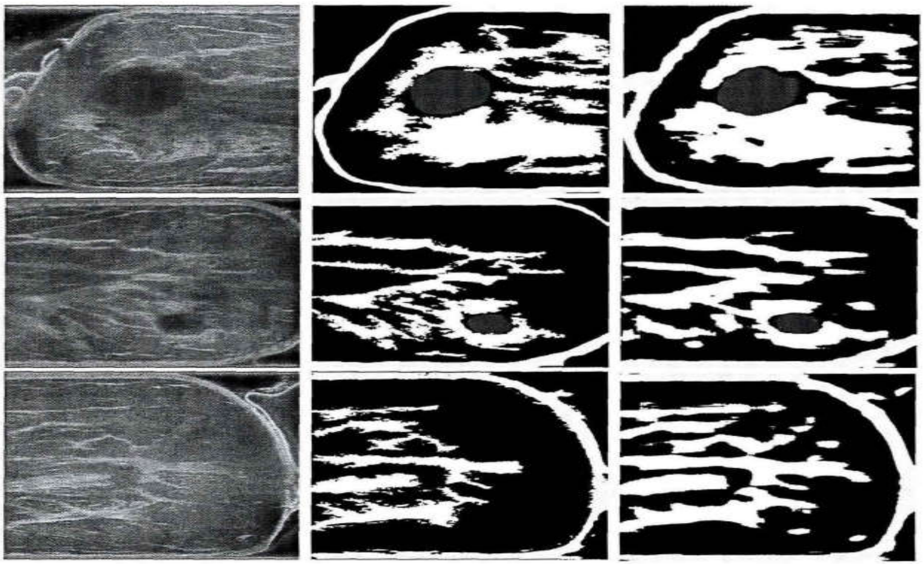

Figure 4. Segmentation results of three breast ultrasound images

In order to compare the contour of the glandular part in the result of the similarity extraction of the shape more intuitively, the result is compared with the hand cut images, as shown in Figure 5.

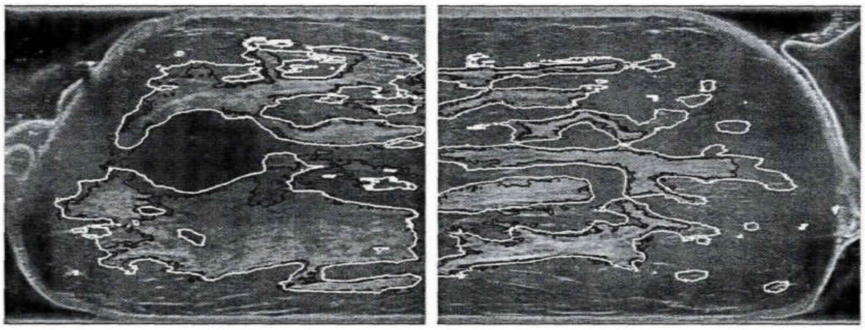

Figure 5. contrast of glandular segmentation of two breast ultrasound images

From the segmentation results, it can be seen that the prediction results of the model are closer to the standard results of hand segmentation by doctors. Most of the tissue regions in the image can be segmented correctly and the shapes are basically the same.

The results of the segmentation are evaluated quantitatively, and the results are shown in Table 2:

Table 2. The quantitative evaluation of image segmentation results

Evaluation Aspects	Accuracy	Precision	Recall	F1-measure
Tumor	0.9947	0.9397	0.9575	0.9485
Gland	0.9013	0.8038	0.8898	0.8446
Skin	0.9720	0.7430	0.9970	0.8515

It can be seen from table 2 that four indexes of tumor segmentation reached 90%, and four indexes of skin and gland segmentation basically reached 80%, which shows that the method proposed in this paper is feasible and effective.

4.3 Experiment analysis

The effect of parameter configuration. In the experiment, the configuration of model parameters has a certain effect on the quality of image segmentation, which is mainly reflected in the size selection of image blocks in input layer of convolutional neural network. A too small size will cause the image block to unable to provide adequate reference information, because the glandular portion of breast ultrasound image and the skin have similar grey value and texture features, to distinguish the two needs to take the surrounding information as a reference; if the size of image block is too large, it will lead to the sample collection goes beyond scope of the original image and create too many samples of invalid information. The larger image block means that the input matrix is larger, which will consume more resources and time of operation. In order to select the size of image block effect on segmentation results, experiments using 5 groups configuration parameters were compared. The size of the input image block is respectively 48, 64, 96, 108 and 128, corresponding to the configuration of the neural network parameters are shown in Table 3, five of which were configured as a convolutional neural network structure. The convolution neural network is constructed using the 5 groups configuration in Table 3. The neural network is trained and divided into the same test image after the training is completed. The result is shown in Figure 6.

Table 3. Five groups of parameters of convolution neural network

Configuration	Group 1	Group 2	Group 3	Group 4	Group 5
Input layer	48×48	64×64	96×96	108×108	128×128
Convolutional layer 1	36@44×44	36@60×60	36@92×92	36@104×104	36@122×122
Pooling layer 1	36@22×22	36@30×30	36@46×46	36@52×52	36@61×61
Convolutional layer 2	36@18×18	36@26×26	36@42×42	36@48×48	36@56×56
Pooling layer 2	36@9×9	36@13×13	36@21×21	36@24×24	36@28×28
Convolutional layer 3	36@6×6	36@9×9	36@18×18	36@21×21	36@24×24
Pooling layer 3	36@2×2	36@3×3	36@6×6	36@7×7	36@8×8
The connection layer	1024	1024	1024	1024	1024
Output layer	4	4	4	4	4

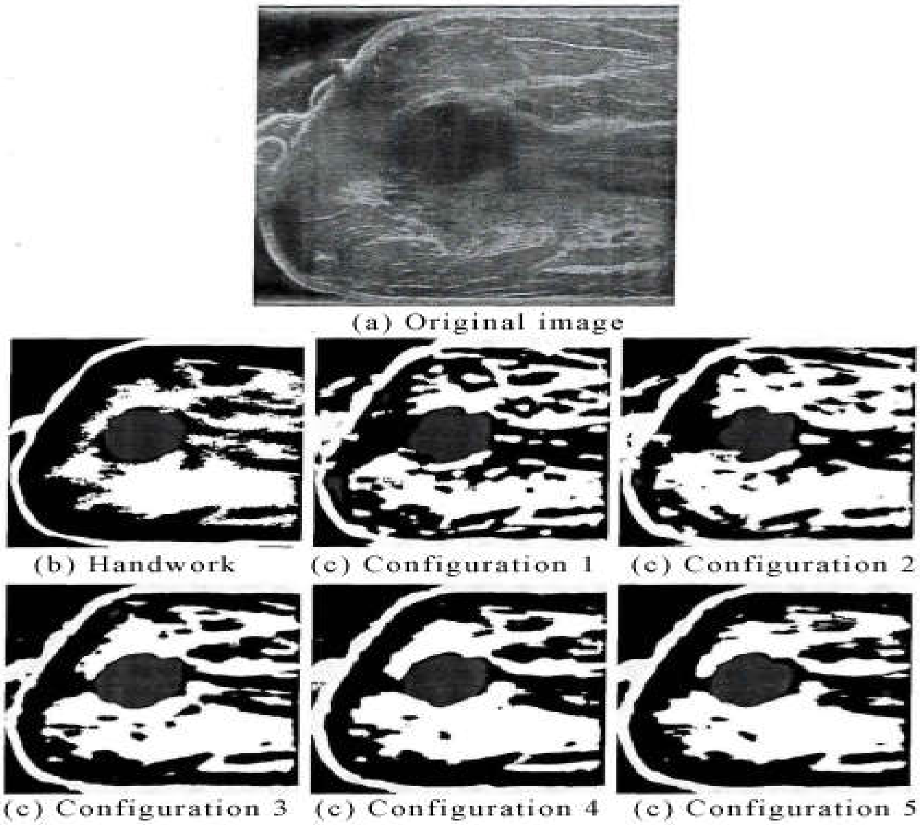

Figure 6. Segmentation results comparison of the 5 sets of configurations

Qualitative analysis of the segmentation results shown in Figure 6 shows that the 5 groups configuration model can basically split images of a tumor right; but when the size of the input image block is smaller, more error appeared in identifying gland using the model; when the image block size is 48*48 and 64*64, part of the image that is a bit complex structure of the skin area was wrongly identified as glands, the glands segmentation area in the image area are significantly more than the standard results in the area of big gland. With the image block size becomes larger, the problem gradually eased. When the image block size is 96*96, it was identified as the glandular region has been significantly smaller in the skin; when the image block size is 108*108, the basic model can correctly distinguish the skin and glands, comparison with the standard results is also similar. In order to further determine the impact of different configurations on the segmentation results, the quantitative analysis of the results of segmentation is needed. The gland tissue is the most complex structure in the ultrasound image of the mammary gland. The results of the segmentation of the gland part are compared quantitatively below. The results are shown in Table 4.

From the results of quantitative analysis, it can be seen that when using the network structure, that is, the size of the input image block is 128*128, the model achieves the best effect in segmentation of breast ultrasound images. When the size of input image is enlarged from 108*108 to 128*128, the segmentation accuracy is not improved. Considering the reduction of invalid image information and the increase of computation efficiency, the size of input image blocks is not further expanded.

Table 4. The quantitative comparison of the results of the 5 groups of segmentation

Evaluation Aspects	Accuracy	Precision	Recall	F1-measure	HD
Configuration 1	0.8451	0.7225	0.7899	0.7543	159.154
Configuration 2	0.8208	0.6535	0.8643	0.7443	166.433
Configuration 3	0.8956	0.7837	0.9031	0.8392	143.450
Configuration 4	0.8984	0.7943	0.8949	0.8416	59.666
Configuration 5	0.9014	0.8038	0.8898	0.8446	59.034

Compare with other methods.

In order to better verify the segmentation effect of the proposed method, the method is compared with the traditional K mean algorithm and the algorithm proposed in the literature. Figure 7 and figure 8 show the use of this method, the mean K algorithm (K=3) method and the literature of two images of breast ultrasound image segmentation results, which is the original image (a), (b) is the standard result, (C) is the use of K means algorithm, (d) is segmentation result using literature method, (e) is the segmentation result using method. Comparison of three kinds of segmentation methods: K algorithm gathers into 3 classes pixel points in the image according to the grey value. Each class representing the specific organizations needs to be identified, the segmentation result of skin and glands belong to the same category; the literature method using threshold method for regional classification, each region can be determined on behalf of the organization but it was still unable to separate the skin and glands: This paper presents the method of using neural network as the classification of each pixel in the picture classifier, can be determined for each category specific representative of the organization, for training the neural network when the skin and glands as two kinds of samples, so this method can distinguish the image the skin and gland area. From the comparison diagram of three methods, it can be seen that the segmentation results obtained in this paper are closer to the manual segmentation standard results, which shows that the proposed algorithm can achieve better results in segmentation of breast ultrasound images.

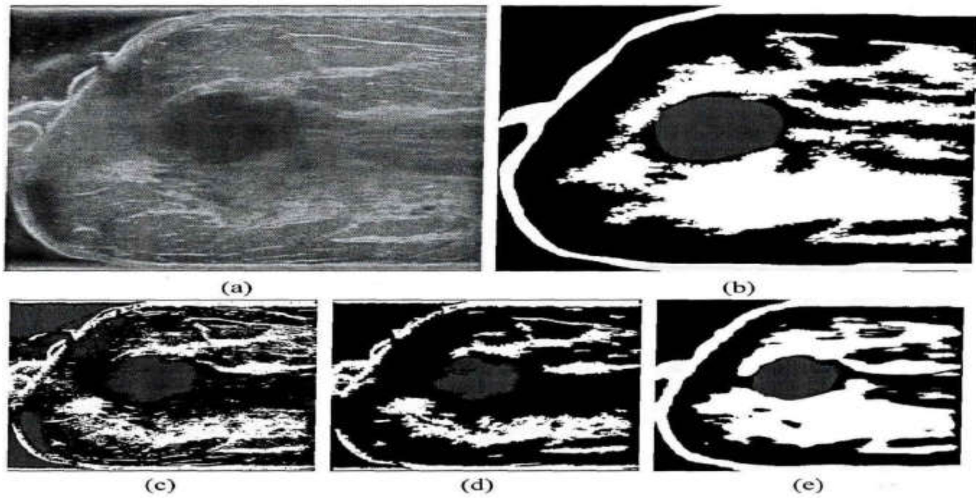

Figure 7. Segmentation results of the tumor images by the three methods

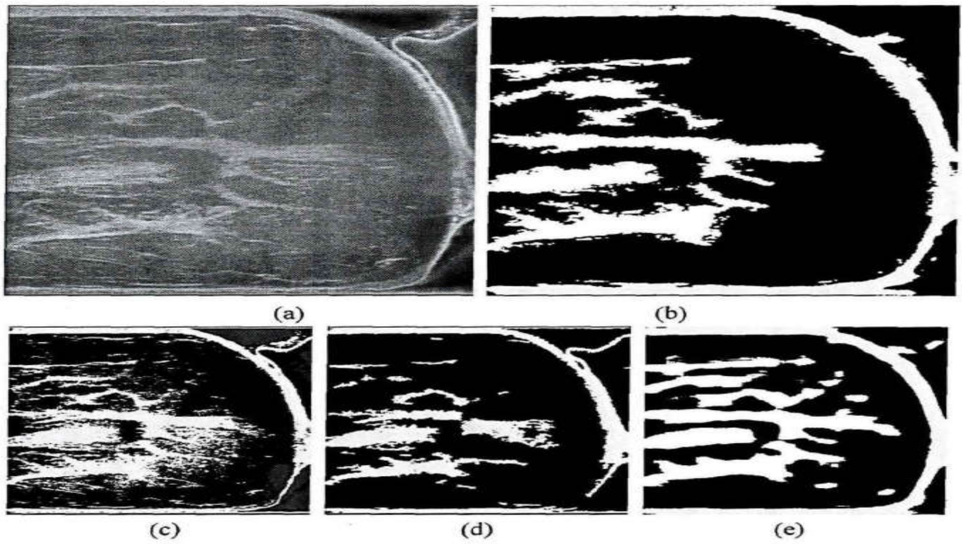

Figure 8. Segmentation results of the non-tumor images by the three methods

5. CONCLUSION

In this paper, combined with the convolution neural network algorithm in the field of deep learning, an automatic segmentation method for breast ultrasound images is proposed, which transforms the image segmentation task into the classification task of each pixel in the image. In the proposed method, according to the doctor's label collection of a large number of samples, select the image block as the convolution neural network input with the characteristics of the pixel as the center, the actual type pixel is represented as the actual value for comparison; then the design of convolutional neural network as the classifier, train the sample data, a higher accuracy can be achieved in the final test set. When the trained model is used to separate the ultrasound image, the classification of each pixel point by pixel blocks can be obtained and also the final segmentation result. The method proposed in this paper can correctly distinguish the tissue area of skin, gland and tumor in breast ultrasound image. The shape and contour are similar to the standard results manually labelled by doctors and have achieved good results in various quantitative evaluation indexes. In the experiment, the segmentation results generated by different neural network parameter configurations are compared, pick out the optimal model, and compare it with other methods, which show that the method proposed in this paper has certain advantages.

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